Morphology Independent Feature Engineering in Motion Capture Database for Gesture Evaluation

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ABSTRACT

In the recent domain of motion capture and analysis, a new challenge has been the automatic evaluation of skill in gestures. Many methods have been proposed for gesture evaluation based on feature extraction, skill modeling and gesture comparison. However, movements can be influenced by many factors other than skill, including morphology. All these influences make comparison between gestures of different people difficult. In this paper, we propose a new method based on constrained linear regression to remove the influence of morphology on motion features. To validate our method, we compare it to a baseline method, consisting in a scaling of the skeleton data [14]. Results show that our method outperforms previous work both in removing morphology influence on feature, and in improving feature relation with skill. For a set of 326 features extracted from two datasets of Taijiquan gestures, we show that morphology influence is completely removed for 100% of the features using our method, whereas the baseline method only allows limited reduction of morphology influence for 74% of the features. Our method improves correlation with skill as assessed by an expert by 0.04 ($p < 0.0001$) in average for 98% of the features, against 0.001 ($p = 0.68$) for 58% of the features with the baseline method. Our method is also more general than previous work, as it could potentially be applied with any interindividual factor on any feature.

CCS CONCEPTS

• **Information systems** → **Content analysis and feature selection**; • **Theory of computation** → **Data modeling**; • **Computing methodologies** → **Motion capture**; Factor analysis;

KEYWORDS

Motion Capture, Feature Extraction, Morphology, Factor Independence, Gesture Evaluation, Linear Regression, Residue

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1 INTRODUCTION

The development of motion capture technologies has unleashed research possibilities in many areas, including robotics, medicine, human computer interaction, games and education. One of the outstanding challenges is the analysis, recognition and more particularly evaluation of skill. Gesture evaluation is essential in many disciplines, and has already been explored in different areas, including sports [9, 13, 16], music [4], dance [1, 6], rehabilitation [12], driving [17] and even surgery [8]. Regardless of the discipline, the typical approach to evaluating a gesture can be divided in four main steps:

- First, motion data must be captured. A database is recorded, generally including several individuals with different skill levels, for instance professionals or teachers and learners.
- Secondly, from these raw motion data, relevant features must be extracted. These features aim to represent movement in an efficient way regarding the targeted task. They can be derived for instance from body kinematics, kinetics, and frequency analysis. They can also represent higher-level relations based on prior domain-knowledge and semantic interpretation, such as expressivity, biomechanics, ergonomics or functionality [2, 7, 10, 11].
- Thirdly, features can be analyzed for selection of the best feature set for the targeted task. A common technique for multi-factor dependent data such as a motion capture database is factor analysis [15]. The goal of this step is to reduce the global amount of information contained in the database to keep the most relevant and reliable information regarding the targeted task. For instance, this step enables to discard unwanted bias, such as morphology, age or expression, while keeping features more dependent on the targeted factor, i.e. skill.
- Finally, the selected features are used to evaluate the gesture. A score can be directly derived from the features and provide an index of the quality of the gesture [12]. Another way is to compute a similarity measure between the features and a model [4, 9].

The problem of feature selection is that it removes information contained in non-selected features. In a motion capture database, many factors may influence features, including psychological, social or physiological factors. The goal of this work is to reduce the influence of some of these factors on the data, to improve the information related to the targeted factor. Morphology is a factor that has a direct influence on motion, making comparisons between gestures of different individuals difficult. To alleviate this issue, different motion data representations have been proposed. Sie et al. [14] proposed a simple skeleton scaling method, by placing the coordinate system on a reference node of the body (i.e. on the pelvis), and dividing all nodes coordinates by the torso height. Features can then be extracted on these scaled data. This method was later used by Morel et al. [9] for evaluation of tennis serve. It has the advantage to be very simple, but has many limitations. It is based on the simplistic hypothesis that the movement of a short individual should be an homothety of those of a tall individual. However, weight, height of the center of mass, shoulder width, and hips width, among others, may also influence movement in different ways, including inertia, balance, speed and power. These characteristics will be altered by this basic scaling.

Kulpa et al. [5] developed a morphology-invariant representation of motion, originally developed for animation, where they defined imbs with variable lengths. Each limb (legs and arms) is defined by the position of its end-effector, and by a plane where the middle joint (knee and elbow) is located. The spine is represented as a spline. This representation allows reconstruction of the movement to fit specific constraints. However, it does not fully store the actual movement, and it modifies it to fit these constraints. It is relevant for animation and motion retrieval, but is not suited for movement analysis, which can require details of the movement that are lost in this representation.

Müller et al. [10] proposed a specific feature set based on 40 logical relational features, originally developed for whole-body motion classification and retrieval. E.g., these relations may correspond to a foot being raised, a hand being in front of the body, legs being crossed, etc. The boundaries for the logical decision are defined by different body segment lengths such as the humerus length or the shoulders width, so that each feature is scaled by a custom pre-defined body characteristic. However, these features do not represent the whole movement of the body, and they do not allow extraction of higher-level features.

In this paper, we propose a method to remove the influence of morphology in a motion capture database right after the feature extraction step, i.e. before the feature selection step. Our method estimates and removes the correlation between a feature and a morphology factor, independently of raw spatial skeleton data. It allows avoidance of direct manipulation of spatial skeleton data that alters body characteristics. The estimated relationship is based on linear regression of individual means and standard deviations of features with morphological factors, which is more general than basic individual scaling. Our method can be seen as a tuning of each feature, to extract more relevant information for a targeted task, before the feature selection step. Our method is also more general than previous work, as it could theoretically be used with any factor and on any feature, whereas related work is limited to the morphology factor.

2 METHOD

The objective of the proposed method is to remove the component of the data distribution resulting from the influence of interindividual factors such as morphology. In order to assess the influence of a morphological factor on a feature, we identify the best linear combination of this factor to approximate the statistics of the feature. For that purpose, constrained linear regression was used.

In a database of F features, containing N samples from I individuals, for each feature $f \in \{1, ..., F\}$ and each individual $i \in \{1, ..., I\}$, let:

$$x_f(n), n \in \{1, ..., N\}$$
$$x_{f,i}(n_i), n_i \in \{1, ..., N_i\}$$
$$x_f = \{x_{f,i}, ..., x_{f,I}\}$$

denote the samples (x_f) of a feature f and subsamples ($x_{f,i}$) of a feature f and an individual i. Let:

$$\mu_f(i) = mean(x_{f,i})$$
$$\sigma_f(i) = std(x_{f,i})$$

denote the mean (μ_f) and standard deviation (σ_f) of a feature f for individual i, and let $m(i)$ denote the morphological factor of individual i. For each statistic of the feature (μ_f, σ_f), a linear regression is performed with the regressor m, i.e. the morphological factor:

$$\mu_{pred,f} = \beta_{0_{\mu,f}} + \beta_{1_{\mu,f}} \cdot m \quad (1)$$
$$\sigma_{pred,f} = \beta_{0_{\sigma,f}} + \beta_{1_{\sigma,f}} \cdot m \quad (2)$$

where $\beta_{0_{\mu,f}}$ and $\beta_{1_{\mu,f}}$ (resp. $\beta_{0_{\sigma,f}}$ and $\beta_{1_{\sigma,f}}$) are the intercept and slope of the linear regression of individual means μ_f (resp. individual standard deviations σ_f).

To ensure positive predictions for the standard deviation ($\sigma_{pred,f}$), the slope parameter ($\beta_{1_{\sigma,f}}$) is constrained so that:

$$\alpha = argmin_i(\sigma_{pred,f}(i))$$
$$\sigma_{pred,f}(\alpha) > 0 \Leftrightarrow \beta_{1_{\sigma,f}} > \frac{-\beta_{0_{\sigma,f}}}{m(\alpha)}$$

A negative standard deviation would lead to physically meaningless data.

The feature engineering method is then based on the hypothesis that the prediction of the linear regression is the part of the statistic (μ_f or σ_f) that can be fully described by the factor, while the residue is the uncorrelated part of the statistic, i.e. the part that is not influenced by the morphological factor. The residues ($\mu_{res,f}$ and $\sigma_{res,f}$) of the predictions are expressed as:

$$\mu_{res,f}(i) = \mu_f(i) - \mu_{pred,f}(i) \quad (3)$$
$$\sigma_{res,f}(i) = \frac{\sigma_f(i)}{\sigma_{pred,f}(i)} \quad (4)$$

The following equation is then used to compute a version of the feature x_f corresponding to these residual statistics, where the influence of morphology has been removed:

$$x_{res,f,i} = \frac{(x_{f,i} - \mu_f(i))}{\sigma_f(i)} \cdot \sigma_{res,f}(i) + \mu_{res,f}(i) \quad (5)$$
$$x_{res,f} = \{x_{res,f,1}, ..., x_{res,f,I}\} \quad (6)$$

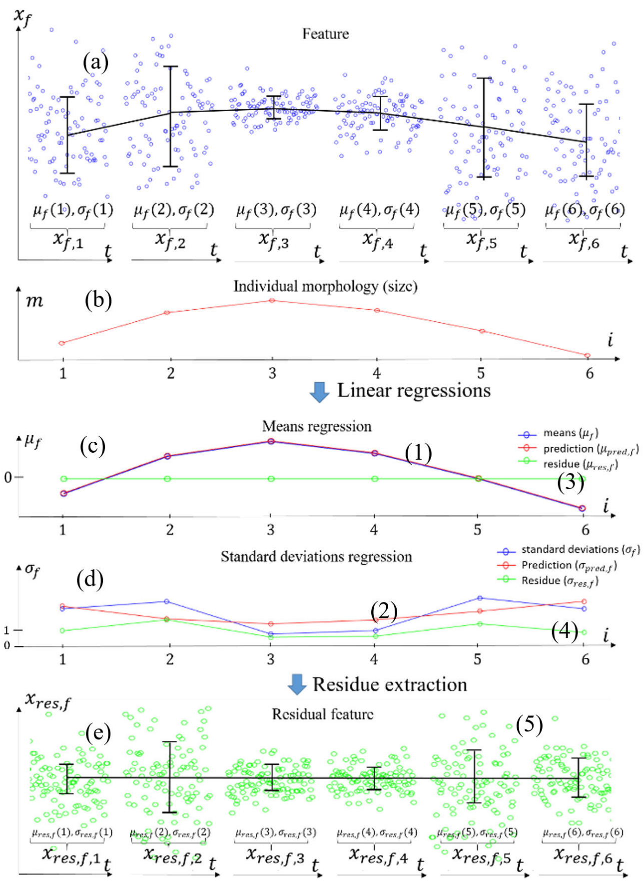

Figure 1: Interindividual factor independent feature extraction. Graph a: feature and individual statistics (μ_f and σ_f). Graph b: individual morphology. Graphs c and d: linear regression of means and standard deviations. The blue curve is the regressand (μ_f or σ_f), the red curve is the prediction (Eq. 1 and 2), and the green curve is the residue (Eq. 3 and 4). Graph e: residual feature extraction (Eq. 5).

where $x_{f,i}$ and $x_{res,f,i}$ are the subsamples of x_f and $x_{res,f}$ corresponding to individual i. Equation 5 can be interpreted as follows: for each individual, the subsamples $x_{f,i}$ are first standardized to remove their initial mean ($\mu_f(i)$) and standard deviation ($\sigma_f(i)$), and then scaled and translated so that their mean and standard deviation correspond to $\mu_{res,f}(i)$ and $\sigma_{res,f}(i)$.

Figure 1 illustrates the extraction of such residues, on an example dataset consisting of six individuals ($I = 6$). This number was arbitrarily used for illustration, but in real situation, more individuals are required to avoid overfitting of the linear regression. The first graph (a) displays an example feature, where data are parameterized with individual means and standard deviations (μ_f and σ_f). The second graph (b) shows the morphological factor m, representing for instance the size of each individual. The third and fourth graphs (c and d) respectively show the results of linear regression of μ_f and σ_f with the regressor m. The blue curve is the regressand (μ_f or σ_f), the red curve is the prediction (Eq. 1 and 2), and the green curve is the residue (Eq. 3 and 4). The final graph (e) then displays the result of the residual feature extraction, where individual means ($\mu_{res,f}$) and standard deviations ($\sigma_{res,f}$) are now independent of the morphology (Eq. 5).

When the residual features are extracted, a correlation analysis can be performed with the factor of interest, e.g. individual skill. As skill is supposedly not correlated to morphology, we can expect that the process will not decrease the correlation between features and skill, but on the contrary, could increase it.

If the features were normalized before the process, they should be normalized again afterwards, as global mean and standard deviation may have changed.

In the remainder of the paper, our method will be referred to as Morphology Independent Residual Feature Extraction or MIRFE.

3 RESULTS

An analysis was conducted on several feature sets extracted from a MoCap database of Taijiquan gestures to validate our method. The results are compared to the baseline method, i.e. skeleton data scaling [14]. In this baseline method, all global joint coordinates are divided by the size of the individual before feature extraction. Section 3.1 presents the datasets used for the validation. The feature sets extracted from the data are then described in Section 3.2. Section 3.3 explains how the morphological factor is represented for the analysis. Finally, Section 3.4 presents a correlation analysis of features statistics (μ_f and σ_f) with morphology and skill factors.

3.1 Datasets

The database used to validate our work is composed of 12 individuals (8 females and 4 males, 50 ± 14 years, 168 ± 12.5 cm, 69.4 ± 16 kg, 11 ± 11 years of practice) performing different Taijiquan gestures. Their movements were recorded at a framerate of 179fps, with a Qualisys optical motion capture system. A total of 68 passive markers were placed on the entire body. All the data were processed to recover missing data due to occlusions, then filtered with a low-pass Butterworth filter with a cutoff frequency of 20Hz. Positions and orientations of 21 anatomical joints were then extracted from the trajectories of the surface markers with the Visual3D™ software. The whole database was then manually segmented.

Two different datasets were extracted from the database:

- Dataset 1: the first dataset is composed of 168 renditions of the gesture 'heel kick' (10 to 16 renditions per individual).
- Dataset 2: the second dataset is composed of 168 renditions of the gesture 'brush knee and twist step' (10 to 16 renditions per individual).

These two gestures were chosen among the database as they are highly distinctive and focus on different body parts. The first gesture (heel kick, see Figure 2) requires balance and synchronicity, and is mainly focused on the lower-body. The second gesture (brush knee and twist step, see Figure 3) is more focused on robustness and force of the whole body, as the individual pushes a virtual adversary with his hand, by transmitting his force from feet to hands.

The global skill of each individual of the database was annotated by three Taijiquan professors, and the skill factor was defined as the average of their annotations.

Figure 2: Heek Kick. [3]

Figure 3: Brush knee and twist step. [3]

3.2 Features

Six different sets of features were extracted from the datasets and tested with the proposed method:

- Global joints trajectories were directly used as a set composed of 63 features, for 21 joints along three dimensions ($F = 63$).
- Local joints trajectories were extracted from global trajectories and orientations. The local trajectory is relative to a local coordinate system placed and oriented according to the parent joint ($F = 63$).
- Global joints trajectories were expressed in a coordinate system stuck on the pelvis. This process allows extraction of more relevant data for comparison between occurrences and individuals, but does not account for the whole body travelling on the capture scene. This feature set is called 'Stuck Global' or 'S. Global' in the rest of the paper ($F = 60$, as pelvis is the origin).
- Local joints trajectories were extracted from stuck global trajectories. This feature set is called 'Stuck Local' or 'S. Local' in the rest of the paper ($F = 60$).
- Müller's feature set [10] consists of 40 features describing geometric relations between body parts that are used originally for motion retrieval. This set of higher-level features is supposed to represent global movements of the full body ($F = 40$).
- Taijiquan ergonomic features inspired by the work of the ergonomist and Taijiquan teacher Eric Caulier [3] were developed as part of the present research, and are the object of a future publication. This feature set is composed of 36 features describing the stability of the body, alignments and optimal angles of body joints, as well as limbs kinematics. These features are inspired from Taijiquan fundamental rules, but can be generalized to other forms of movements, such as music, sport, or working gestures ($F = 36$).

The first four sets are low-level features, representing body joints trajectories over time, and are supposedly very dependent to morphology. On the opposite, the last two sets are higher-level features, based on general a-priori knowledge of human movement, and describing more functional movement characteristics. Still, most Müller features should be strongly influenced by morphology as they are just geometric relations between body parts.

3.3 Factor definition

Morphology can be defined with numerous variables tightly linked together, such as the size or weight of each body segment. To extract the most relevant variable to represent morphology, we performed a PCA on several variables, including individual segment lengths (foot, calf, leg, trunk, arm, forearm, hand and head), hips width, shoulders width, size from feet to head, and size from feet to fingers.

As the first principal component alone explained 76% of the data variance, and as it was almost equivalent to the size from feet to fingers ($R = 0.9932, p = 1.15 \times 10^{-15}$), we decided to keep the size from feet to fingers as the morphology factor. The use of only one variable to represent morphology was done to limit the complexity of the regression model, and thus the risks of overfitting due to the small number of individuals ($I = 12$). This choice is further discussed in Section 4.

3.4 Correlation Analysis

3.4.1 Dataset1 (heel kick).

Morphology. For each feature, absolute correlations ($|R| \in [0-1]$, simply called correlation in the following) of individual statistics (μ_f and σ_f) with morphology are computed, without process, after scaling, after MIRFE process, and after combination of scaling and MIRFE process. Figure 4 (resp. Figure 5) shows boxplots representing these correlations for μ_f (resp. σ_f), for each feature set. We can observe that each feature set seems globally quite influenced by morphology (see first graph, Figure 4 and Figure 5), especially low-level features (global and local trajectories), and Müller features. On the other hand, Taijiquan ergonomic rules seem to be somewhat intrinsically less influenced by morphology. We can see in Figure 4 and Figure 5 that the MIRFE method almost removes all influence of morphology on feature means and standard deviations. It is clearly not the case with the scaling method, which merely decreases morphology influence on features means. Table 1 shows the mean reduction of correlations of features individual statistics with morphology, for each method. Scaling method reduces this morphology correlation by 0.124 for means, and 0.078 for standard deviations. As a comparison, MIRFE removes almost all the present correlation: −0.356 for means and −0.328 for standard deviations. Combination of both methods give the same results as MIRFE alone. We can conclude that MIRFE removes morphology influence much better than scaling for any feature set.

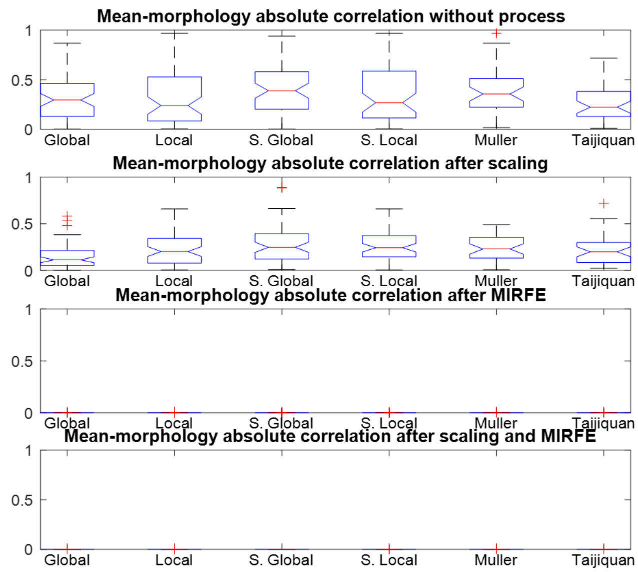

Figure 4: Correlation analysis of feature means with morphology factor: 1. without process; 2. after scaling; 3. after MIRFE; 4. after scaling and MIRFE. (dataset 1)

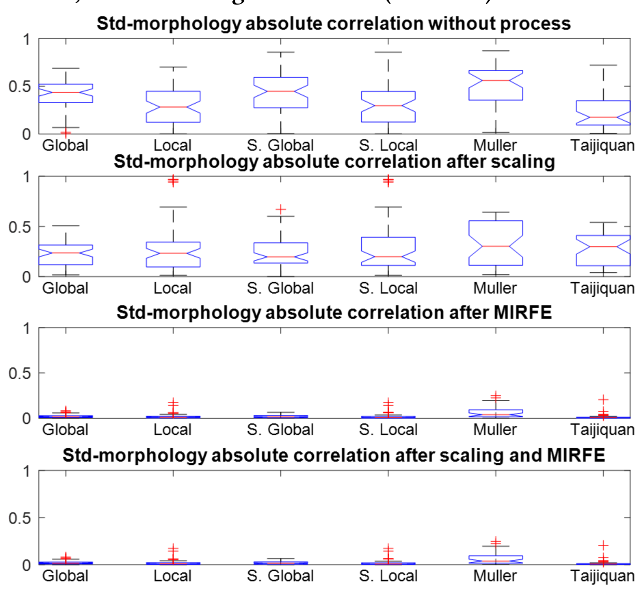

Figure 5: Correlation analysis of feature standard deviations with morphology factor: 1. without process; 2. after scaling; 3. after MIRFE; 4. after scaling and MIRFE. (dataset 1)

Skill. For each feature, correlations of individual statistics (μ_f and σ_f) with skill are computed, without process, after scaling, after MIRFE process, and after combination of scaling and MIRFE process. Figure 6 (resp. Figure 7) shows boxplots representing these correlations for μ_f (resp. σ_f) without process for each feature set, and the improvement[1] of these correlations after each method. All feature sets seem globally correlated to skill without any process (see first graph, Figure 6 and Figure 7). Local trajectory means seem generally less correlated to skill[2]. For both means and standard deviations, and for all feature sets, scaling seems to increase correlation with skill for some features, but it also seems to decrease it for others (see second graph, Figure 6 and Figure 7). Table 2 shows the mean improvement of correlations between individual features means and skill. Except for Taijiquan feature set, MIRFE alone improves the relation to skill better than scaling, and better than combination of both methods. The best improvement of mean-skill correlations

Table 1: Mean reduction of feature individual statistics-morphology correlations for all features (dataset 1). $*: p < 0.05, **: p < 0.01, ***: p < 0.001$

	Means	Standard deviations
Scaling	-0.124***	-0.078***
MIRFE	-0.356***	-0.328***
Scaling + MIRFE	-0.356***	-0.328***

Table 2: Mean improvement of individual mean-skill correlation for each feature set (dataset 1)

	Global	Local	S. Global	S. Local	Müller	Taijiquan
Scaling	0.03**	0.02*	0.015*	0.02*	0.02**	0.03 (p=0.08)
MIRFE	0.045***	0.04***	0.05***	0.04***	0.07***	0.03***
Scaling + MIRFE	0.035***	0.03***	0.035***	0.03**	0.045***	0.04*

Table 3: Ratio of positive (>-0.005) improvement of individual mean-skill correlation for each feature set (dataset 1)

	Global	Local	S. Global	S. Local	Müller	Taijiquan
Scaling	0.86	0.62	0.67	0.57	0.77	0.83
MIRFE	0.98	0.98	0.98	0.97	1	0.98
Scaling + MIRFE	0.87	0.70	0.82	0.67	0.82	0.85

Table 4: Mean improvement of feature individual statistics-skill correlations for all features (dataset 1)

	Means	Standard deviations
Scaling	0.022***	0.003(p=0.47)
MIRFE	0.044***	0.027***

Table 5: Ratio of positive (>-0.005) improvement of feature individual statistics-skill correlations for all features (dataset 1)

	Means	Standard deviations
Scaling	0.71	0.65
MIRFE	0.98	0.75

[1] The improvement of correlation is simply defined as the difference of these correlations without process and after process for each of the compared methods.

[2] Note that it does not mean that local trajectories are less relevant than global trajectories to evaluate skill. Global trajectories may have globally higher correlations with skill, but there are probably more redundancies among them.

Table 6: Mean reduction of feature individual statistics-morphology correlations for all features (dataset 2)

	Means	Standard deviations
Scaling	-0.126***	-0.054***
MIRFE	-0.365***	-0.296***

Table 7: Ratio of negative (<0.005) reduction of feature individual statistics-morphology correlations for all features (dataset 2)

	Means	Standard deviations
Scaling	0.74	0.71
MIRFE	1.00	0.99

Table 8: Mean improvement of feature individual statistics-skill correlations for all features (dataset 2)

	Means	Standard deviations
Scaling	0.001(p=0.68)	-0.008(p=0.17)
MIRFE	0.043***	0.022***

Table 9: Ratio of positive (>-0.005) improvement of feature individual statistics-skill correlations for all features (dataset 2)

	Means	Standard deviations
Scaling	0.58	0.59
MIRFE	0.98	0.77

was obtained for Müller's feature set, where mean-skill correlation is increased by 0.07 in average.

Table 4 and Table 5 give global results of scaling and MIRFE methods, accounting for all features. The MIRFE method outperforms scaling both for individual means and standard deviations correlations with skill. The MIRFE method improves the relation of features with skill for most features (98% for mean and 75% for standard deviation, see Table 5). On the opposite, scaling can have adverse effects on the features (i.e. degradation of skill influence, see Table 5, and second graph, Figure 6 and Figure 7). Though, for both methods, the improvement can be important for some features, increasing correlations with skill up to 0.4, and thus showing the interest of the use of these methods before any feature selection step.

3.4.2 Dataset 2 (Brush knee and twist step). The same process as for dataset 1 was performed on the second dataset. Similar results were obtained for morphology influence reduction, as shown in Table 6 and Table 7. The scaling method merely reduced morphology influence (−0.126 for means, and −0.054 for standard deviations) compared to MIRFE, which almost removes all correlation with morphology for all features. Moreover, scaling only reduced morphology influence for 74% of the features, regarding means, and 71% regarding standard deviations (see Table 7). It means the morphology influence can even be worsened (i.e. increased) by the

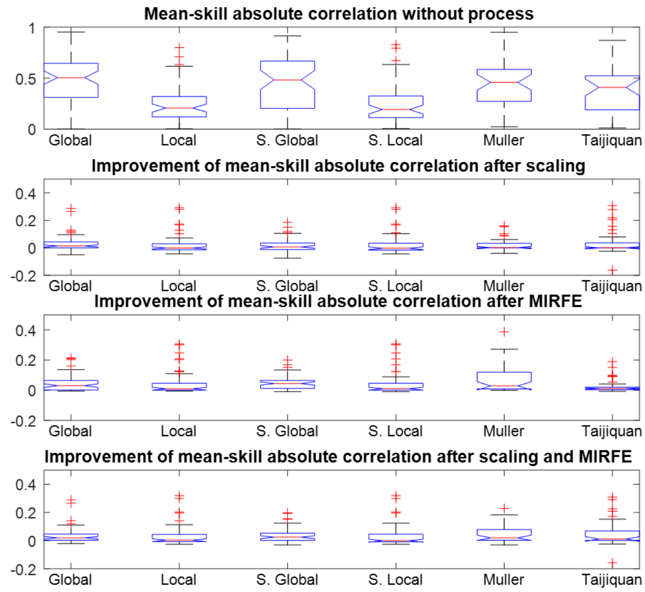

Figure 6: Correlation analysis of feature means with skill factor: 1. Correlation without process; 2. Improvement after scaling; 3. Improvement after MIRFE; 4. Improvement after scaling and MIRFE.

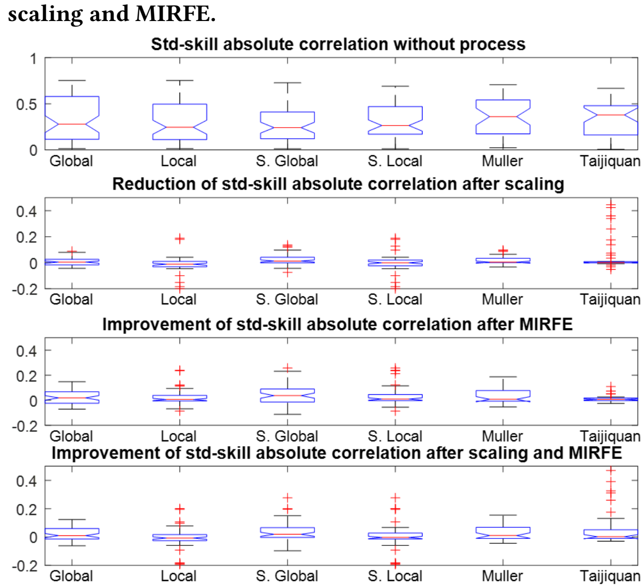

Figure 7: Correlation analysis of feature standard deviations with skill factor: 1. without process; 2. after scaling; 3. after MIRFE; 4. after scaling and MIRFE. (dataset 1)

scaling method in other cases (i.e. for 26% and 29% of the features respectively regarding means and standard deviations).

Table 8 and Table 9 respectively show the average improvement, and the ratio of positive improvement of skill influence for all features. Scaling does not improve the skill influence at all for this dataset. On the opposite, MIRFE improves skill influence for both feature means (+0.043) and standard deviations (+0.022), and for almost all features (see Table 9).

4 DISCUSSION

The results show that our MIRFE method allows to remove almost completely the morphological influence on the features (at least for one morphological factor). We show that, by removing morphology influence, we can improve features relations with other factors, such as skill. This method could be used to improve analysis of the influence of many other interindividual factors than skill on movement, such as expression, fatigue, illness, age, etc. Unlike other methods based on direct skeleton data manipulation, our method could also be generalized to reduce unwanted influence of different factors, such as age or sex. However, morphology has a direct influence on motion, with a clearer relation, than age or sex, and is thus more appropriate for this method. Nonetheless, unlike previously proposed approaches, our method can easily be used with any morphological factor, such as weight, hip width or shoulder stature.

Another drawback of direct skeleton data manipulation, such as basic scaling or skeleton representation adaptation, is that they only consider spatial variability due to morphology. In fact, motion is a spatiotemporal series, and morphology may also have an influence on time, because of body inertia for instance. As our method can be applied to any feature, it can be used on kinematic or kinetic features too. Our method is based on simple linear regression, but could be generalized to more complex methods, such as multiple linear or non-linear regression with several interindividual factors. However, more complex methods also lead to more risk of overfitting. In our case, the number of individuals was small ($I = 12$), which would probably be insufficient for more complex methods. Overfitting of our residual feature extraction method would lead to almost no residue, i.e. insufficient information in the residual features. This limitation is owing to the specific domain of the study, i.e. movement analysis. Indeed, data acquisition in that domain is still particularly constraining and time-consuming with the current state-of-the-art technologies, limiting the size of databases. Our method could be applied to other multi-factor dependent databases in less constraining domains, such as speech for instance. Feature selection could directly be used instead of our method, by selecting features less dependent of morphology, and more related to skill, using for instance factor analysis. However, any feature selection method would inevitably lead to the loss of information contained in all unselected features. On the opposite, our method aims to reduce unnecessary information (related to unwanted factors) by tuning, but keeping, all features. A feature selection process can then be performed on the tuned features.

Our validation method is based on correlation analysis. More advanced methods could be used, such as gesture recognition/evaluation methods, and verifying if our method improves the evaluation, by comparing it to skill annotations. This is left as a prospect for future research.

5 CONCLUSION

In this paper, we presented an original method allowing extraction of morphology independent features from a motion capture database. This method is based on constrained linear regression with any morphological factor on individual means and standard deviations of features. The residues of these regressions allow extraction of residual features, independent of morphology. We showed that our method efficiently removes morphology influence, and consequently improves relation with other factors, such as motor skill. Our method outperforms previous work both for morphology independence and skill relation improvement. It is also more general than related work, as it can be used with any interindividual factor, and on any feature. Our method could be adapted with more complex models than linear regression, but would require larger databases. As a prospect of future work, the proposed method will be tested on different gesture evaluation techniques.

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REFERENCES

[1] Andreas Aristidou, Efstathios Stavrakis, Panayiotis Charalambous, Yiorgos Chrysanthou, and Stephania Loizidou Himona. 2015. Folk dance evaluation using Laban Movement Analysis. *Journal on Computing and Cultural Heritage (JOCCH)* 8, 4 (2015), 20.

[2] SM Bruijn, OG Meijer, PJ Beek, and JH Van Dieën. 2013. Assessing the stability of human locomotion: a review of current measures. *Journal of the Royal Society Interface* 10, 83 (2013), 20120999.

[3] Éric Caulier. 2010. *Comprendre le taijiquan*. Vol. 1. Editions Modulaires Européennes InterCommunication SPRL.

[4] Lei Chen, Sylvie Gibet, Pierre-François Marteau, Fabrice Marandola, and Marcelo M Wanderley. 2016. Quantitative Evaluation of Percussive Gestures by Ranking Trainees versus Teacher. In *Proceedings of the 3rd International Symposium on Movement and Computing*. ACM, 13.

[5] R Kulpa, F Multon, and Bruno Arnaldi. 2005. Morphology-independent representation of motions for interactive human-like animation. In *Computer Graphics Forum*, Vol. 24. Wiley Online Library, 343–351.

[6] Sohaib Laraba and Joëlle Tilmanne. 2016. Dance performance evaluation using hidden Markov models. *Computer Animation and Virtual Worlds* 27, 3-4 (2016), 321–329.

[7] Caroline Larboulette and Sylvie Gibet. 2015. A review of computable expressive descriptors of human motion. In *Proceedings of the 2nd International Workshop on Movement and Computing*. ACM, 21–28.

[8] Giuseppe Megali, Stefano Sinigaglia, Oliver Tonet, and Paolo Dario. 2006. Modelling and evaluation of surgical performance using hidden Markov models. *IEEE Transactions on Biomedical Engineering* 53, 10 (2006), 1911–1919.

[9] Marion Morel, Richard Kulpa, Anthony Sorel, Catherine Achard, and Séverine Dubuisson. 2016. Automatic and Generic Evaluation of Spatial and Temporal Errors in Sport Motions. In *11th International Conference on Computer Vision Theory and Applications (VISAPP 2016)*. 542–551.

[10] Meinard Müller and Tido Röder. 2006. Motion templates for automatic classification and retrieval of motion capture data. In *Proceedings of the 2006 ACM SIGGRAPH/Eurographics symposium on Computer animation*. Eurographics Association, 137–146.

[11] Franck Multon and Anne-Hélène Olivier. 2013. Biomechanics of walking in real world: naturalness we wish to reach in virtual reality. In *Human Walking in Virtual Environments*. Springer, 55–77.

[12] Trieu Pham, Pubudu N Pathirana, Yonggwan Won, and Saiyi Li. 2016. A summative scoring system for evaluation of human kinematic performance. *Biomedical Signal Processing and Control* 23 (2016), 85–92.

[13] Otniel Portillo-Rodriguez, Oscar O Sandoval-Gonzalez, Carlo Avizzano, Emanuele Ruffaldi, and Massimo Bergamasco. 2010. Capturing and training motor skills. In *Human-Robot Interaction*. InTech.

[14] Mu-Syuan Sie, Yu-Chuan Cheng, and Cheng-Chin Chiang. 2014. Key motion spotting in continuous motion sequences using motion sensing devices. In *Signal Processing, Communications and Computing (ICSPCC), 2014 IEEE International*

Conference on. IEEE, 326–331.

[15] Mickaël Tits, Joëlle Tilmanne, and Nicolas d'Alessandro. 2016. A Novel Tool for Motion Capture Database Factor Statistical Exploration. In *Proceedings of the 3rd International Symposium on Movement and Computing*. ACM, 2.

[16] Matteo Zago, Marina Codari, F Marcello Iaia, and Chiarella Sforza. 2016. Multi-segmental movements as a function of experience in karate. *Journal of Sports Sciences* (2016), 1–8.

[17] Yilu Zhang, William C Lin, and Yuen-Kwok Steve Chin. 2010. A pattern-recognition approach for driving skill characterization. *IEEE transactions on intelligent transportation systems* 11, 4 (2010), 905–916.